Int J Life Cycle Assess (2012) 17:696–705
DOI 10.1007/s11367-012-0413-z

UNCERTAINTIES IN LCA

Uncertainty in environmentally conscious decision making: beer or wine?

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Received: 19 August 2011 / Accepted: 14 March 2012 / Published online: 30 March 2012

Abstract
Purpose Life cycle assessment (LCA) is being used increasingly in decision support situations. In actual cases, the sources of uncertainty are easily hidden in the complexity. Methods for taking uncertainty into account are recommended by LCA guidelines, but actual application remains rare. The aim of this study is to demonstrate the sources of uncertainty in a practical simple selection case wherein a customer makes a decision between beer and wine in a restaurant, considering the selected criteria and the given information. The uncertainty in LCA results is connected to the broader scope of decision analysis.
Methods Life cycle inventories were collected for beer and wine production from existing literature. The functional unit was chosen to be one serving of alcohol: beer or wine. For illustrative purposes, only the global warming potential indicator was included in the LCA through carbon footprint (CF). Probabilistic uncertainty analysis was applied to the CF system using Monte Carlo simulation. Water footprint was also roughly considered. In addition, three non-environmental indicators were included in the decision: weight control, price, and taste. The comparison between the two products was constructed as a multiple-criteria decision analytical problem.
Results and discussion The results indicated that beer had, on average, a higher CF value than wine did. However, the difference was not significant, and within the uncertainty range, also the opposite conclusion was possible. The ratio of wine to beer CF was dominated by the uncertainty in the N_2O emissions of wine production. When all of the decision criteria were included, the level of uncertainty prevented robust overall conclusions about preference for beer or wine. However, depending on the utility differences assigned to subjective indicators, there existed also cases wherein decisions could be made at a 10 % risk level regardless of high overall uncertainty.
Conclusions In many cases, the uncertainties of LCA are dwarfed by the overall uncertainty of the decision situation. However, as shown by our example, in many cases, reasonable decisions can be made in spite of high uncertainties. The uncertainties of single LCA indicators should be considered in relation to the decision-making problem, which depends on the uncertainty of LCA indicators but also significantly on the weighting of the indicators and the related uncertainty. Successful decision making depends on both the magnitude of uncertainty and the differences in expected utility value between alternatives. More attention should be paid to uncertainty analysis considering the weighting factors.

Keywords Beer · Carbon footprint · Consumer choice · Life cycle assessment · Monte Carlo simulation · Multiple-criteria decision analysis · Uncertainty · Weighting

Responsible editor: Niels Jungbluth

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1 Introduction

The study of uncertainty in life cycle assessment (LCA) has become an important research topic in recent years. Uncertainty is present in all LCA results, and in some cases, its magnitude may be so great that it hinders the drawing of robust conclusions. Several methods for controlling and quantifying uncertainty have been developed (Williams et al. 2009; Huijbregts 2001; Lloyd and Ries 2007). Commonly uncertainty is classified into three subcategories: parameter uncertainty, scenario uncertainty, and model uncertainty. Of these, parameter uncertainty is the most frequently studied subject, and methods such as Monte Carlo simulation, analytical uncertainty propagation, fuzzy logic, and Bayesian reasoning are being applied with increasing frequency (Lloyd and Ries 2007).

However the topic of uncertainty in environmentally conscious decision making is much broader than the commonly applied methods imply. It cannot be reduced to error estimations or cutoff analysis (Williams et al. 2009; Lenzen 2001). It encompasses not only the life cycle inventory (LCI) stage but also the goal and scope, impact assessment, and interpretation stages. Uncertainty in the goal definition and interpretation stages can later surface in discussion of whether consequential (CLCA) or attributional (ALCA) methods should be used. Guidance documents can reduce this type of uncertainty by limiting the types of questions that can be answered with a certain kind of LCA approach (ILCD 2010), but considerable uncertainty is still present in the interpretation stages.

Uncertainty is not a problem inherent only to LCA. It is encountered in virtually all decision-making situations with incomplete information. In these cases, a good decision cannot guarantee a preferable outcome, so risk tolerance becomes an issue (Keeney and Raiffa 1993). For example, carrying an umbrella just in case the weather forecasts are wrong may be a good or bad decision, depending not on the outcome (rain or no rain) but on the rationality of the decision itself (what was at stake and whether the probabilities were correctly assessed).

In environmental and health policy, uncertainty has been deliberately fabricated to slow down regulation of tobacco and greenhouse gas emissions for example (Michaels 2008). In the field of LCA, similar discussions of uncertainty have been observed in the dichotomy between CLCA and attributional LCAALCA (Weidema 2009; Ekvall and Weidema 2004; Heijungs and Guinee 2007) and in the discussion of indirect land use change for biofuels (Cherubini et al. 2009). In consequence, modelers in environmental decision making are using more and more uncertainty and sensitivity analysis tools to test what level of uncertainty is tolerable for a given decision (Saltelli et al. 2008). In general, the magnitude of uncertainty is not important while the influence of that uncertainty on the decision is (Saltelli et al. 2008). This aspect of interpretation of the LCA results in actual decision contexts has been discussed much less than the quantitatively less problematic aspects of stochastic error propagation.

Life cycle analysis has a long history in the decision analysis context. Multiple-criteria decision analysis (MCDA) is used in the weighting of indicator results to form an overall sustainability score (Finnveden et al. 2009), but few studies have examined the role of environmental indicators in the larger decision setting. The aim of this study is to explore the nature of uncertainty when incomplete LCA results are used in parallel with other indicators to inform a practical decision. The decision to be modeled is the selection between two alcoholic beverages in a restaurant: one serving of beer or wine. Five decision criteria are considered: carbon and water footprint, energy content, price, and the subjective taste of the products. The fundamental research question to be addressed is whether the consumer can make the decision with the given uncertainty for the selected criteria in view of the selected risk level. In many real-life situations, LCA results are not the dominant criterion on which the decision is made. Therefore, the situation is framed as a general MCDA problem (Keeney and Raiffa 1993). The aim of the study is not to argue as to which of the products actually performs better in terms of the selected decision criteria but, rather, to use the case study as an illustrative example. The case study is deliberately chosen to be simple, but we believe that some of the results derived from it can be generalized to other, more complex and environmentally relevant situations, such as house design, automobile selection, energy scenarios, and use of biomass.

2 Materials and methods

2.1 Description of the decision situation: beer or wine?

The hypothetical decision-making situation is constructed for a consumer aiming to select between beer and wine as a beverage in a restaurant. It is further assumed that the decision is based on readily available public information provided to the consumer and on subjective assessments. It is assumed also that the consumer is literate in LCA terms and that a quantitative assessment of the LCA uncertainty outcome is communicated to the consumer. For further simplification of the problem, it is assumed that the restaurant offers only a single type of beer (a lager) and a single type of wine (a Spanish red). The beverage alternatives are limited by what is available at the restaurant. This narrows the decision to an MCDA problem with five decision criteria: carbon and water footprint, energy content, price, and product taste (Fig. 1).

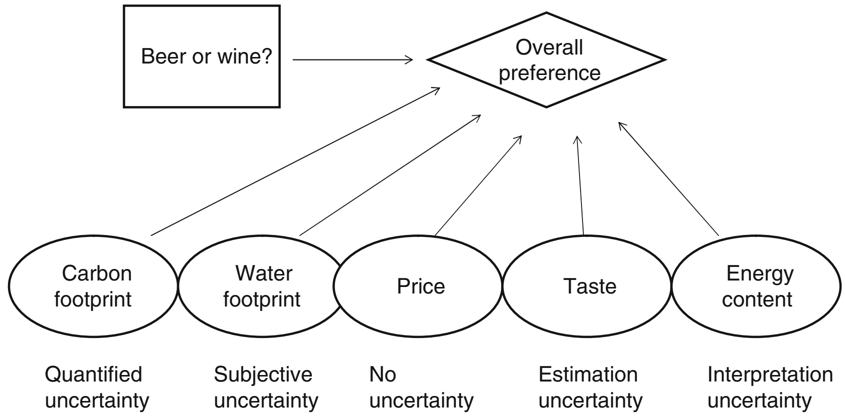

Fig. 1 The decision-making framework for a customer choosing an alcoholic beverage at a restaurant. The alcohol content of the two beverages was considered to be the same and therefore not used as a decision-making criterion. The types of uncertainty are listed for the individual indicators

We claim that this decision problem can be thought of as a general example of the application of LCA results in decision making. Usually concern for the environment is just one aspect of the decision criteria, and also other criteria involve considerable uncertainty. The price and subjective taste of the beverage probably dominate in the selection of a beverage. Of these, the price is typically known with certainty before the decision, but the taste can only be subjectively estimated. The consumer might also consider health issues, such as avoiding the risks of obesity (Keeney 2008). The energy content of the beverages can be known with high precision before the decision, but overall impact on avoidance of obesity is highly uncertain. This uncertainty should be represented in the interpretation of weights.

First, the uncertainty for the selected decision-making criteria was determined. From an LCA perspective, the goal and scope of the case study were narrowed to a single product selection. ALCA was chosen as the basis for inventory collection, and the inventories were based on current average technologies (ILCD 2010). The functional unit chosen was one restaurant serving corresponding to 1.3 standard drinks (12 g of pure alcohol $\times$ 1.3 = 15.6 g). This corresponded to 33 cl of beer with an alcohol content of 4.72 % and 12 cl of wine with an alcohol content of 13 %. This simplified further analysis since the amount of intoxication could be ignored as a decision criterion.

Carbon footprint (CF) as determined in the ISO 14067 standard (ISO 2011), measured by global warming potential within a 100-year time frame, was chosen as the only indicator in the life cycle impact assessment (LCIA). CF is also currently the most communicated LCA result, so many consumer decisions have to be made with just this one impact category. The uncertainty of not considering all impact categories could be included in the study through Bayesian reasoning but was not, for the sake of simplicity. Water footprint (WF) too was included as an environmental indicator communicated to the consumer. However, it was not included in the LCA, though reported as a separate figure obtained from the Water Footprint Network database (2011a, b). Since no uncertainty ranges for WF have been published, subjective approximation was necessary for taking into account possible inventory problems. As a first approximation, the uncertainty factors (UFs) presented in the ecoinvent database for land use were used as a proxy (i.e., UF = 1.5; ecoinvent 2010).

2.2 Parametric uncertainty in LCI and LCIA

The life cycle inventories of beer and wine were unbalanced in terms of their detail. The beer case study (Fig. 2) was constructed from Finnish primary data on barley, fertilizers, pesticides, and lime production and use in line with the work of Soimakallio et al. (2009), as well as from environmental reports of breweries based on material from Carlsberg Breweries (2004). In comparison, the wine case (see Fig. 2) was based on a peer-reviewed publication (Gazulla et al. 2010), which was complemented with transportation data and with detailed uncertainty information concerning the N_2O emissions. The system boundaries of Gazulla were carefully reviewed in order to ensure that similar cutoff criteria and byproduct allocation rules were used in the two studies. However, no guarantee could be made that the system boundaries would be exactly comparable without repetition of the wine study. In the strictest sense, this prevents proper comparison between products. Nevertheless, consumers compare product LCA results without the possibility of evaluating system boundaries. Since the two studies were conducted with similar calculation rules and in a manner conforming to general good practice in LCA, the systems were considered comparable.

Since the purpose was to illustrate the importance of different sources of uncertainty, a coarse estimate for the uncertainty was used. All uncertainties were included with a continuous log-normal distribution with positive range for random variable *X*, and parameterized with the median and an uncertainty factor. We obtained the 95 % confidence interval for the distributions by multiplying and dividing the median with/by the uncertainty factor. This is a relatively common approach in quantification of uncertainty (Frischknecht et al. 2005).

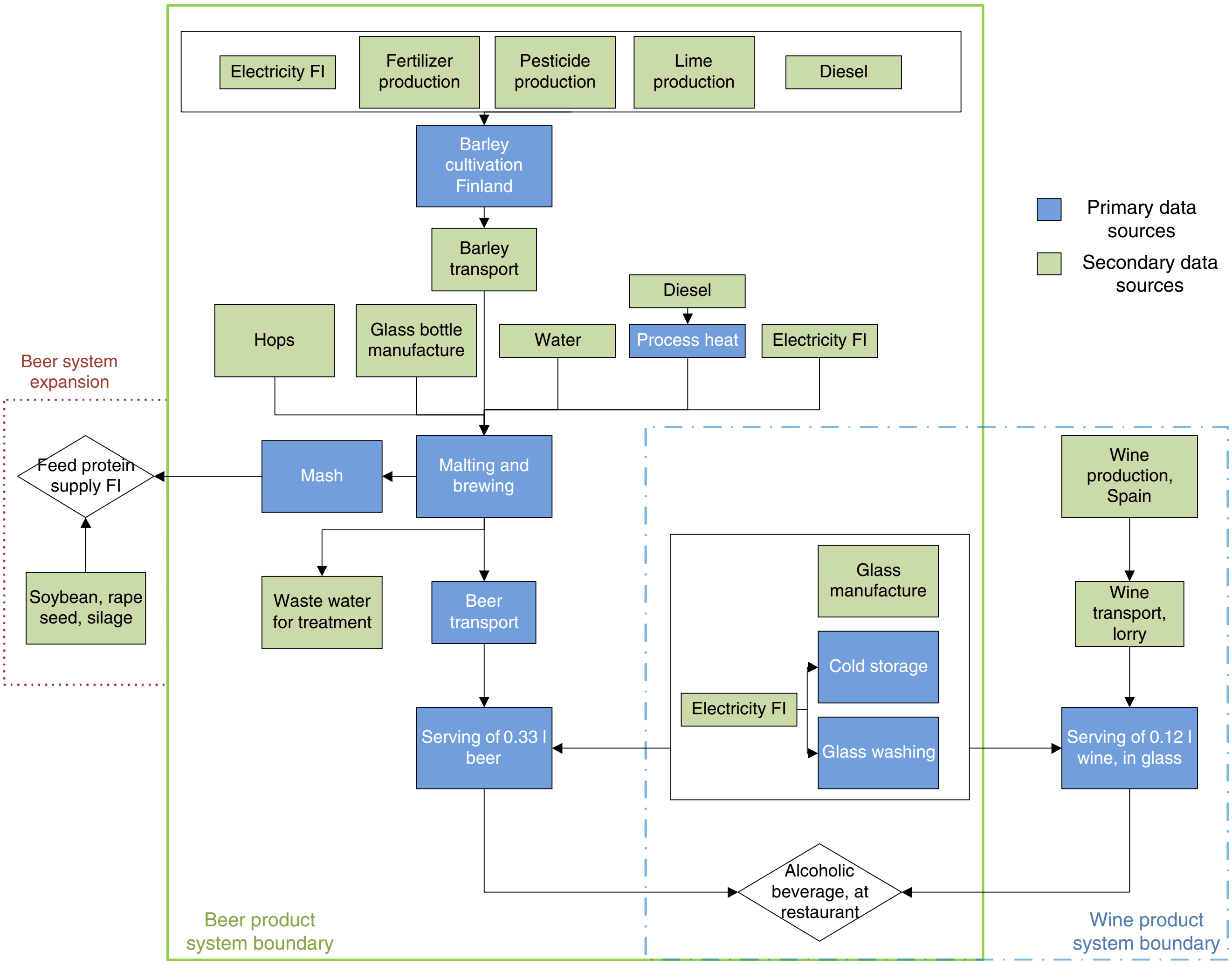

Fig. 2 The system boundary for the beer and the wine product system considered on the basis of the work of Mattila et al. (2011). The *solid line* delimits the beer product system boundary, the *dotted line* on the left the system expansion for the beer product system, and the *dashed line* on the right the wine product system boundary. Some processes belong to both the beer and the wine product system; therefore, the system boundaries overlap

However, as the empirical basis for assigning probability distributions to the model parameters is lacking, the quantification of uncertainty for the simulation of a true but unknown distribution of values would provide more robust estimate of the uncertainty (see, e.g., Hoffman and Hammonds 1993; Plevin et al. 2010). For simplicity, only the log-normal distribution which often describes sufficiently well the distribution of the parameters in environment and ecology (Limpert et al. 2001) was considered here.

In all, 35 sources of parametric uncertainty were included in the Monte Carlo simulation. Three outputs were chosen: the carbon footprint of beer, that of wine, and the ratio of the two. All input variables were assumed to be independent of each other. Uncertainty factor estimates were used for most parameters, with some parameters relying on distributions derived from statistics or found in the literature. The product inputs of agriculture were estimated to have an uncertainty factor of 1.1 (for example, fertilizer nitrogen use of 72–88 kg N/ha). The same low uncertainty factor was used for the process inputs of lime and fertilizer manufacturing and the emission intensity of grain transportation trucks. Pesticide production emissions were assumed to have a higher uncertainty factor (at UF=1.6). The diesel use of agriculture was included with a broad uncertainty factor (110–150 l/ha), corresponding to the variation in the tillage options available (Soimakallio et al. 2009). Similarly, the range in pesticide use was very wide, reflecting variations in agricultural practices: 0.8–2.0 l/ha (Soimakallio et al. 2009). The yield of barley was modeled to be 3,050–4,020 kg/ha on the basis of the variation in statistical yields (FAO 2010). The emissions of diesel refining had a range of 470–570 g CO_2 eq./l (Soimakallio et al. 2009). The greenhouse gas (GHG) emissions from fertilizer production were considered to be highly variable, on the basis of the range of state-of-the-art production and the

European average (2.9–6.8 kg CO_2 eq./kg N). The transportation of beer and wine to the restaurant was assumed to be done with trucks carrying a 9-t payload with highly uncertain transport distances and emission factors [an uncertainty factor of 1.3 was applied to the emission factors taken from the Lipasto database (VTT 2011)]. Electricity production was included through addition of variation based on the work of Soimakallio and Saikku (2012) to the average emission intensity of electricity production in Finland in accordance with ecoinvent (2010) figures, resulting in a value of 190–330 g CO_2/kWh. In line with the ecoinvent uncertainty factors, a UF of 1.5 was assigned to the emissions of CH_4 and N_2O from combustion. The emissions from wastewater treatment were considered to be highly uncertain, with a UF of 2.

The GHG emissions from soil were included with very high uncertainty factors (UF=4). The emissions from transformation of land use from soy cultivation, replaced with the byproduct mash, were assumed to range from 200 to 2,300 g CO_2/kg (ecoinvent 2010). The N_2O emissions from fertilizer use were also included, with a range of 0.5–8 % of N_2O from application of N fertilizer, representing the typical range in Finland (Soimakallio et al. 2009). The range was assumed to be independent for barley, wine grapes, and soy, since the method of N application and environmental conditions are different (barley in boreal, wine in Mediterranean, and soy in tropical ecoregions). The carbon change for barley fields due to tillage was assumed to equal 286 kg CO_2/ha/a in accordance with the work of Soimakallio et al. (2009), with relatively high uncertainty (UF=2).

For the wine LCI, an overall uncertainty factor was used to reflect the variability in the published LCI results—i.e., 750–900 g CO_2 eq./bottle (Gazulla et al. 2010). In addition, the N_2O emissions from soil were treated similarly to those in barley cultivation, with an uncertainty factor of 4. The N_2O emissions from wine cultivation were assigned a value of 500 g CO_2 eq./bottle (Gazulla et al. 2010), which was varied between 125 and 2,000 g CO_2 eq. per bottle in view of the full uncertainty in N_2O emissions. The uncertainty factor is similar for wine and barley N_2O emissions, but no guarantee can be made that the N_2O emissions of wine cultivation would be dependent on the N_2O emitted in barley cultivation (perennial vs. annual plants, different climate, and different fertilizer). Therefore, the uncertainties were considered to be independent.

The serving of the beverages showed some relatively high uncertainties. For example, the number of drinking glasses used in emptying a 0.75-l wine bottle was assumed to be anywhere between 1 and 5. Similarly, the percentage of glasses broken during any single use was assumed to be 0.5–2 % for both beverages. The electricity use of appliances was unknown; therefore, a modern energy rating (A+) was chosen as the reference, and the electricity consumption figure was varied by a factor of 2. The LCI of packaging of glass items from ecoinvent (2010) includes considerable variability between regions; therefore, the full spread of the LCI results was used, resulting in a UF of 1.25.

In addition to the LCI parameters, the uncertainty inherent in the LCIA factors was included. An uncertainty factor of 1.4 was applied to the direct radiative forcing factors for N_2O and CH_4 (Huijbregts et al. 2003), resulting in characterization factors of 18–35 kg/kg for CH_4 and 213–417 kg/kg for N_2O.

The uncertainties were propagated with the Simulación 4.0 add-in of MS Excel, with 2,000 iterations (addition of iterations beyond that did not influence the distributions). Sensitivity analysis was conducted via scatterplots of the results and multivariate analysis. The uncertainties shared by the two product systems were screened from the comparison through simultaneous calculation of both CF figures for each Monte Carlo sampling and subsequent calculation of their ratio. For example, the CF of beer and wine was calculated with a given N_2O characterization factor and the results were compared. Then another characterization factor was sampled (along with other parameters), and the calculation was repeated. This made the ratios of the CFs dependent on all of the common uncertain parameters. Since all input parameters were assumed to be independent of each other, no covariance analysis was deemed necessary.

2.3 Uncertainties in the consumer decision

Uncertainties in environmentally conscious decision making were illustrated through a numerical example related to the decision problem of a consumer selecting a drink, between beer and wine. It was assumed that the consumer is interested in evaluating characteristics between the two decision alternatives by means of the following five decision criteria: CF, WF, weight control (WC), price (P), and taste (T). The aim of the decision maker (i.e., the consumer) was to select the decision alternative that maximizes overall utility from his or her perspective with respect to all five decision criteria simultaneously.

Overall utility was analyzed via multicriteria decision analysis techniques (e.g., Saaty 1980; Keeney and Raiffa 1993). In MCDA, the utility model consists of multiple decision criteria with subjective weights describing their relative importance and, second, decision alternatives and their performance with respect to each decision criterion. The uncertainties involved in the MCDA model were analyzed by means of statistical models and Monte Carlo simulation techniques (Leskinen and Kangas 1998; Alho et al. 2001) that take into account the correlation structures of the multicriteria model (due to scaling of the utility indices, for example). The statistical approach has been applied by Leskinen et al. (2006) and Leskinen (2008), for example. The practical implementation of the Monte Carlo simulations was carried out with the STEPS software (Haara and Leskinen

2007). Analysis was based on so-called ratio scale utility measures as applied also in the Analytic Hierarchy Process (Saaty 1980). We used a thousand sampling iterations to define the output distributions. This number was found to be sufficient since the addition of further iterations did not change the results.

For CF, the ratio was set on the basis of the results calculated in this paper and explained in Section 2.2. It was assumed that the consumer is informed of the uncertainty ranges for the products. For the water footprint, only the average ratio (1.2/1) is known; this is based on the reported water footprints (99 l for beer and 120 l for wine; Water Footprint Network 2011a, b). Therefore, the consumer has to evaluate the significance of the uncertainty in the water footprint subjectively. For sensitivity analysis, a log-normal distribution for the ratio was assumed, with several options for the standard deviation: (a) uncertainty equal to 50 % of the STD of CF, (b) uncertainty equal to the STD of CF, and (c) uncertainty at the level of twice the STD of CF.

The energy content of beer and wine was known with certainty from food composition data (KTL 2010), so it was considered to be deterministic with a ratio of 1.69/1, with wine having the lower caloric content (i.e., being better).

For price and taste, several combinations were assumed. First, it was assumed that the price ratio was 1/1 (i.e., equally expensive alternatives) and that the taste ratio was 1.1/1 such that the consumer has a slight preference for beer. Second, it was assumed that the price ratio was 1/2 (i.e., beer more expensive) and the taste ratio 4/1 (i.e., the consumer having a strong preference for the taste of beer). In both cases, it was assumed that the price ratio was deterministic and that the subjective taste ratio had a log-normal distribution, with three different parameter values for STD (similar to the sensitivity analysis for WF). In addition, combinations of 1/1 with 4/1 and 1/2 with 1.1/1 for the price and taste utility ratio, respectively, were tested.

In addition to taste, the decision criteria weights are subjective. They describe how important the various criteria are in view of decision-maker preferences. Six individual weight combinations were tested; first, it was assumed that all criteria have equal weight, and, second, it was assumed that each of the five decision criteria, in turn, has 10 times the weight of the other criteria. In all six cases, it was assumed that the weight ratios have log-normal distributions, with three different parameter values for STD (again, similarly to WF).

3 Results and discussion

3.1 Comparison of the carbon footprints and main sources of uncertainty

As could be expected, the CF inventory results showed considerable overlap (Fig. 3). Therefore, no clear distinction between the beverages could be drawn on the basis of carbon footprint information. Statistical testing of the distributions was impossible, since they were not independent (i.e., they included the same sources of uncertainty). Even when the common uncertainty sources were screened out (by consideration of the ratio of the carbon footprints in each simulation run), the ratio of the CFs varied between 0.5 and 1.7 (median of 1.14). Since the 95 % confidence interval for the distribution of the rations included 1.0, it could not be stated with any significance that either option would be preferable. This is a common outcome in LCA: depending on the parameter selection, either option might be better (Lloyd and Ries 2007).

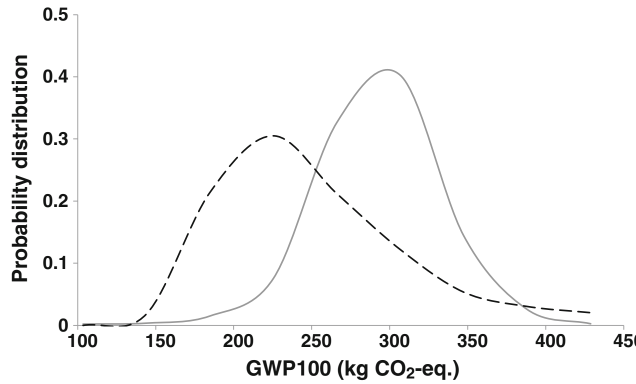

Fig. 3 A comparison of the carbon footprints of beer (*solid line*) and wine (*dashed line*)

A sensitivity analysis was then conducted to identify the main components of the uncertainty. The contribution of each variable was assessed with Spearman's rank correlations (ρ) between the input variable and the ratio of the carbon footprints. The Spearman's rank correlation represents how well the relationship between variables can be described by a monotonic function, resulting in a Spearman's correlation between −1 and 1. The results (Fig. 4) show that the ratio of wine to beer CF was dominated by the uncertainty in (a) the N_2O emissions of wine production (ρ=0.82), (b) CO_2 emissions of soybean land transformation avoided (ρ=0.30), and (c) the LCI results for bottle production—with the LCI of wine production and the N_2O emissions of soybean and barley cultivation having a minor effect. The rank correlations between input coefficients are not presented, since they were assumed to be independent of each other.

The dependence of the overall conclusion on the uncertainty of N_2O emissions is a troublesome issue, since this matter cannot be fully resolved through more accurate measurements. The science related to the magnitude of N_2O emissions from fertilizer application is still not resolved (e.g., Crutzen et al. 2008). While N_2O emissions can be measured in a given field in given conditions with great precision, generalization to agricultural system level remains uncertain. The emissions

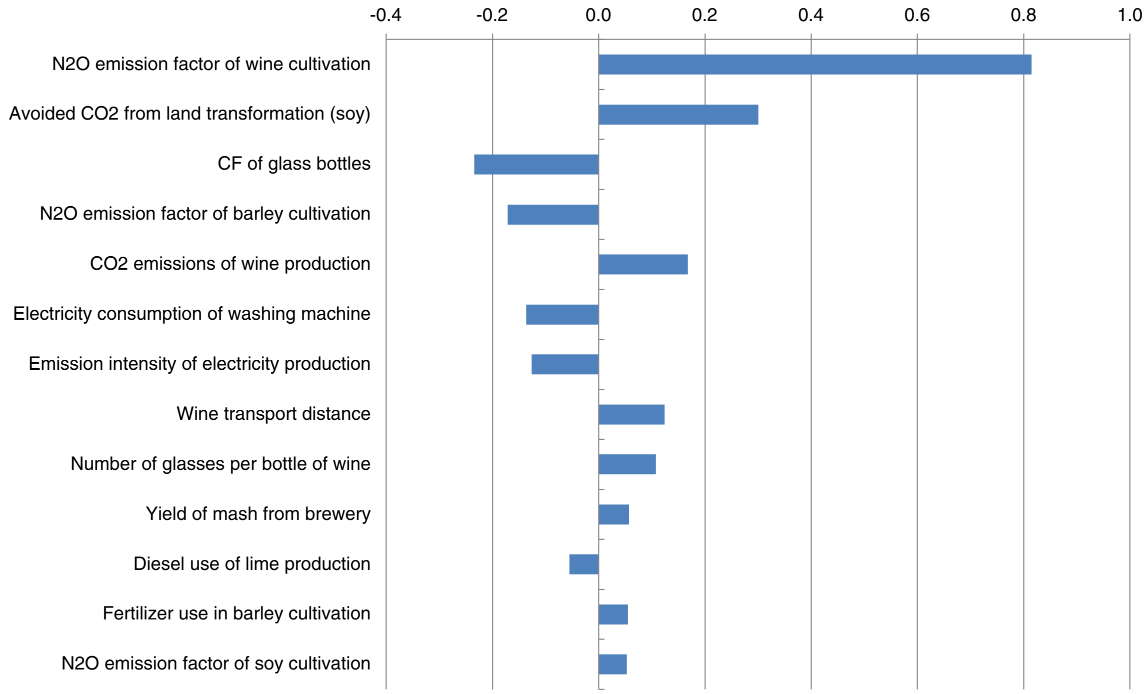

Fig. 4 Spearman's rank correlations (ρ) between the most important uncertainty variables and the result value for the carbon footprint (*CF*) ratio between beer and wine

may vary hugely with spatial and temporal differences. Therefore, the uncertainty is partially a result of decision rule uncertainty, which cannot be reduced by means of more measurements.

3.2 Uncertainties in the consumer decision

If it is assumed that a consumer makes a decision between beer and wine that is based only on CF, the decision problem is simply to compare the probability distributions of beer and wine CFs. From the analysis presented in Section 3.1, the utility ratio of beer being better than wine with respect to CF has, on a logarithmic scale, a normal distribution with an expected value of −0.114 and standard deviation of 0.323. This indicates that the probability of beer being better than wine is equal to 0.36, so a decision cannot be made with a 10 % risk level, for example.

Cases 1–6 in Table 1 give the results of the Monte Carlo simulations based on 1,000 samples for different parameter combinations, which are designed for examination of what happens to the decision problem if other decision criteria are taken into account in addition to CF. Note that the aim of Table 1 is not to represent a full experimental design in which all relevant parameter combinations are analyzed. Instead, our aim is just to point out that in specific preference structures the consumer can end up reaching completely different conclusions relative to the starting point in which beer is better than wine with a probability of 0.36; i.e., no decision can be made with 10 % risk. In Table 1, the priorities of beer and wine (that of wine is equal to 1 minus the priority of beer) indicate the total utility index of the decision alternatives as calculated from weighted arithmetic average or criterion-specific utility ratios (see, e.g., Saaty 1980). The priorities given are arithmetic averages over the 1,000 random samples. The priorities can be interpreted such that the higher the priority, the better the decision alternative. Moreover, the priorities sum to 1 over the decision alternatives. The probability of beer being better indicates a likelihood that beer's priority index is higher than wine's. The probability of wine being better can be calculated as 1 minus the probability that beer is better. If it is assumed that the decision maker can tolerate 10 % risk, for example, a decision can be made if the probabilities in cases 1–6 are either below 0.1 or above 0.9.

Case 1 in Table 1 indicates that if the uncertainties are low and the price+taste combination is appropriate, the decision maker can choose wine or beer with an acceptable risk level in certain cases. Otherwise, no decisions can be made with the present preference structure and uncertainty level. When CF is given more weight (case 2), the situation is quite similar to case 1. In case 3, greater weight is assigned to a WF that clearly supports beer. On the other hand, uncertainties in many cases prevent decision making with a 10 % risk level. Case 4 gives more weight to weight control, which strongly supports wine. A decision can be made with 10 % risk in all of the cases studied. When price is assigned more weight, wine can be chosen with several parameter combinations (case 5). According greater weight

Table 1 Relative utility indices (priority) and probabilities that beer is better than wine with different uncertainty parameters, and price and taste assumptions, when: (1) all decision criteria have equal weight and (2) carbon footprint (CF), (3) water footprint (WF), (4) weight control (WC), (5) price (P), and (6) taste (T) have 10 times the weight of other decision criteria. The probabilities in boldface indicate that a decision can be made with 10 % risk; for readability, the beer/wine utility ratios are expressed in decimal terms—e.g., if beer was twice as expensive as wine, the beer/wine utility ratio was equal to 0.5

Uncertainty with respect to CF	50 %				100 %				200 %			
Price (beer/wine)	1	1	0.5	0.5	1	1	0.5	0.5	1	1	0.5	0.5
Taste (beer/wine)	1.1	4	1.1	4	1.1	4	1.1	4	1.1	4	1.1	4
1. Equal weight for all												
Priority (beer)	0.48	0.54	0.45	0.50	0.48	0.54	0.45	0.50	0.48	0.54	0.45	0.50
Probability that beer is better	0.18	**0.97**	**0.01**	0.58	0.25	0.87	**0.04**	0.54	0.32	0.74	0.16	0.46
2. CF 10 times the weight of others												
Priority (beer)	0.48	0.50	0.476	0.49	0.48	0.50	0.46	0.48	0.47	0.49	0.46	0.48
Probability that beer is better	0.35	0.47	0.28	0.39	0.34	0.49	0.27	0.37	0.30	0.46	0.27	0.37
3. WF 10 times the weight of others												
Priority (beer)	0.52	0.54	0.51	0.53	0.52	0.54	0.51	0.536	0.52	0.54	0.51	0.52
Probability that beer is better	0.77	**0.91**	0.62	0.87	0.65	0.74	0.54	0.69	0.57	0.67	0.52	0.58
4. WC 10 times the weight of others												
Priority (beer)	0.41	0.43	0.40	0.42	0.41	0.43	0.40	0.42	0.42	0.44	0.40	0.42
Probability that beer is better	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.02**	**0.07**	**0.00**	**0.04**
5. P 10 times the weight of others												
Priority (beer)	0.49	0.51	0.38	0.40	0.49	0.51	0.38	0.40	0.49	0.51	0.38	0.40
Probability that beer is better	0.20	**0.97**	**0.00**	**0.00**	0.25	0.88	**0.00**	**0.00**	0.33	0.68	**0.01**	**0.03**
6. T 10 times the weight of others												
Priority (beer)	0.51	0.71	0.50	0.69	0.51	0.70	0.50	0.69	0.51	0.67	0.49	0.66
Probability that beer is better	0.64	**1.00**	0.45	**1.00**	0.55	**1.00**	0.49	**1.00**	0.54	**0.97**	0.47	**0.94**

to taste supports beer, and a decision could be made with several parameter combinations (case 6).

It can be concluded from Table 1 that the uncertainties were too high for successful decision making with the selected 10 % risk level in several cases (43 cases out of 72). However, there existed also situations wherein a decision could be made (9 cases lead to selection of beer and 20 to selection of wine). This was not possible in the reference case wherein the decision maker uses only CF as a decision criterion. The analysis illustrates that successful decision making depends on both the magnitude of uncertainty and the differences in expected utility value between alternatives. In other words, the level of uncertainty acceptable cannot be determined as such; instead, it depends also on other characteristics of the decision support model and the decision maker's attitude to risk. It is evident too that the optimality of decision alternatives strongly depends on the weight given.

4 Conclusions

The uncertainties in LCA indicators result from normative choices, the stochastic nature of the parameters, and lack of knowledge of the system examined. Despite the fact that the uncertainties are typically significant, they are often excluded from LCA studies. If the uncertainties are not studied, the selections made may turn out to be unfavorable afterwards. If reliable data are not available for a certain parameter or indicator under consideration, that parameter or indicator should not be excluded but, instead, considered with a suitable—i.e., significant enough—uncertainty range.

The uncertainties of individual LCA indicators should be considered in relation to the decision-making problem at hand. The decision-making problem depends on the uncertainty of LCA indicators but also significantly on the weighting of the indicators and the related uncertainty. In general, it cannot be determined whether the uncertainty of a single LCA indicator is significant, and whether the LCA is adequately reliable or not. For example, the choice from among various production methods for a product depends on the uncertainty level, the difference in the average utility ratios of the alternatives, and the attitude of the decision maker toward risk. The weighting of indicators is determined not only by preferences or value systems but also by assumptions as to the overall future state of the environment and the meaningfulness of the decision in question. In many decision-making situations, the related uncertainties

are high but a decision still must be made. Different decision strategies with respect to decision-maker attitudes to risk can be utilized in such situations (e.g., Keeney and Raiffa 1993). The problem is that in practice, the decisions have to be made in limited time, with limited resources, and in the absence of availability of user-friendly and adequately sophisticated programs. The development of such programs is certainly required.

In this paper, we studied the impact of the uncertainties of two environmental indicators (carbon and water footprints) in combination with three other indicators (weight control, price, and taste) in a case study wherein a customer is selecting between two alcoholic beverages in a restaurant: one serving of either beer or wine. Only CF was considered through LCI, and only the stochastic nature of the parameters was considered to influence uncertainty of CF. Comprehensive uncertainty analysis including examination of various normative choices such as selecting the system boundary and allocation methods would have extended the uncertainty range of CF. However, it is possible that the weighting issues should be decided upon in advance, since it is not necessarily meaningful to carry out detailed, complex, comprehensive, and probably costly uncertainty analysis if the relevant LCA indicator is given low weight in decision making.

Acknowledgments The authors wish to acknowledge the FINLCA project of the Finnish Funding Agency for Technology and Innovation for financing. Also, the authors are grateful to Tuomas Helin for drawing Fig. 2 in the paper.

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